RESEARCH ON THE OPTIMIZATION OF PATH INFORMATION IN THE PROCESS OF LOGISTICS DISTRIBUTION BY IMPROVED ANT COLONY ALGORITHM

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Abstract. Whether the logistics distribution path is reasonable determines distribution speed and distribution efficiency. In this research, the ant colony algorithm is introduced in detail, and a mathematical model of the algorithm is established for the characteristics of logistics distribution problems, and the algorithm is further improved and optimized on convergence rate and global searching ability. The experimental results showed that the improved algorithm optimized the logistics distribution path and could find the optimal path scheme quickly and effectively, proving that it is feasible and promising in the optimization of logistics distribution paths.

Keywords: ant colony algorithm, logistics distribution, path optimization.

Introduction

Ant colony algorithm was initially proposed by M. Dorigo [1], which is a heuristic search algorithm [2] based on population optimization that can find the best path to the destination through active feedback and distributed collaboration with a strong vitality. Research and optimization of ant colony algorithm are of great importance to network routing and urban transport systems.

The ant colony algorithm has been involved in many combinatorial optimization problems, from quadratic assignment problem [3], job-shop scheduling problem to protein folding problem and vehicle routing problem [4], which shows its practicability. Though playing a great role in the optimization of logistics distribution, the algorithm faces some difficulties. Qi [5] processed the routing problem of vehicles taking advantages of simulated annealing and ant colony optimization. In the first stage, simulated annealing provided a good initial solution for ant colony optimization. In the second stage, the near-optimal solution was searched in local scope using iterated local search. In this way, the routes of vehicles were optimized, which made logistics management more scientific. In the study of Guo [6], the development of robots and route planning algorithm were analyzed, and the advantages and disadvantages of the traditional intelligent route planning were emphatically studied. The route planning problem of robots was studied using ant colony algorithm, and some solutions were put forward. The largest difficulty is in logistics management actually, as there are more and more limitations and requirements on transport and distribution plans [7]. If different search options were used, the results obtained will vary. Chang et al. [8] put forward a multi-objective genetic algorithm based on greedy search which could regulate the allocation of available resources and automatically generate various feasible emergency logistics schedules for decision-makers to minimize the logistics time and cost in distribution planning and made an optimization analysis on logistics management using different algorithms.

As the algorithm is applied in practice more and more frequently, the system complexity increases [9], with more and more data to be processed, under which circumstance single or one or two intelligent methods cannot well solve problems. Hence, in this design, we improved the algorithm and carried out simulation analysis to solve the path optimization problem of logistics distribution, hoping to develop optimal transport and distribution plans, saving time and consumption.

1. Ant colony algorithm

1.1 Principle and basic model of the algorithm

In nature, ants are randomly distributed. Once an ant finds food, it will leave a pheromone trail before returning to the nest, following which other ants can find the food. In this way, the pheromones on the path will be gradually strengthened. Nevertheless, as time goes by, the pheromones begin to evaporate and the appeal falls, resulting in a longer time for other ants to follow the trail to find food. As a result, shorter paths are more favorable for ants to follow, leaving a greater pheromone density on the paths. In addition, pheromone can avoid convergence to local optimal solution [10]. If there is no evaporation at all, the path which the first ant seeks will be too attractive, which will limit the exploration of solutions.

In general, when an ant finds a good path from the nest to the food source (ie, a short path), the other ants are more likely to follow the path, eventually leading all the ants to follow the path. The idea of ant colony algorithm is to solve problems by simulating the behavior of ants [11]. The basic steps of the ant colony algorithm are as follows:

Set the number of ants in the ant colony to be Q, the distance between client i and j to be d_{ij} and degree of intimacy, visibility, between them to be x_{ij}, $\eta_{ij} = 1/d_{ij}$, the heromone concentration between them to be τ_{ij}. Then, at time point t, the probability of ant k to move from client i to client j is as follows:

$$p_{ij}^{k}(t) = \frac{\tau_{ij}(t)^{\alpha} \cdot \eta_{ij}(t)^{\beta}}{\sum_{k \in A_k} \tau_{ik}(t)^{\alpha} \cdot \eta_{ik}(t)^{\beta}}, j \in A_k, 0, j \notin A_k. \tag{1}$$

Where A_k refers to a collection of customer points that have not yet been accessed, which is changing in the evolution process. α, β refer to the roles of pheromones and heuristic factors accumulated in movement in path selection. The pheromone update rules on the relevant path are as follows:

$$\tau_{ij}(t+n) = \rho \cdot \tau_{ij}(t) + \Delta\tau_{ij}, \tag{2}$$

$$\Delta\tau_{ij}(t+x) = \sum_{k=1}^{Q} \Delta\tau_{ij}^{k}. \tag{3}$$

Where ρ refers to the information retention level.

Taking a twin bridge model as an example, suppose that the remaining pheromones of ants are proportional to the number of ants in an asymmetric bridge. Meanwhile, suppose a short bridge to be A and a long bridge to be B and A_m and B_m respectively refer to the number of ants that cross the bridges ($A_m + B_m = m$). If the ants arrive at the front of the two bridges, then the probability of crossing bridge A by the $m+1$ time is as below:

$$P_A(m) = \frac{(A_m + k)^k}{(A_m + k)^k + (B_m + k)^k}. \tag{4}$$

Where A and B are parameters that are used to match the actual data, and the probability meets the following condition:

$$P_B(m) = 1 - P_A(m). \tag{5}$$

1.2 Improvement and optimization of ant colony algorithm

The genetic algorithm begins with a solution to the group problem, and each group contains a certain number of individuals [12], and the entities of these individuals are genetically encoded. The algorithm simplifies the situation that the coding work is based on the theory of "survival of the fittest" and is repeated until an approximate optimal solution is found. Genetic algorithms are mainly used for selection, crossover and variant operations [13] and evolve and generate new generations according to optimization principles. Besides, it performs selection of functions based on the degree of fitness and crosses the parental body to produce new individuals on which mutation is realized, which is circulated until the best solution is produced.

The ant colony algorithm has a global search function and can be combined with other algorithms, with good adaptability and robustness as well as good parallel processing performance. However, the algorithm is prone to be restricted to the local best solution and tends to be affected by initial parameters [14]. Similarly, the genetic algorithm has strong adaptability and versatility, global optimization performance and parallel processing performance, it also has good scalability. Hence, the combination of the two algorithms is conductive to improve the convergence rate of the algorithm.

Symbol definition: $s_{i,j}$ refers to the distance between client i and client $j(i,j = 0,1,2,\dots,L)$, when $i,j = 0$, it refers to the distribution center; S_k refers to the maximum travel distance of vehicle k; n_k refers to the number of customers assigned to vehicle k, when $n_k = 0$, it means that vehicle k is not involved in distribution; G_k refers to a collection of customer points of vehicle $k(k = 1,2,\dots,K)$, when $n_k = 0, G_k = \emptyset$, when $n_k \neq 0$, $\{r_k^1, r_k^2, \dots, r_{k^k}^n \subset \{1,2,\dots,L\}$, where g_k^i indicates that the order of the customer point in the distribution line of vehicle k is i.

The constraint condition of the optimized algorithm is:

$$1) \sum_{i=1}^{n_k} q_{r_k^i} \leq Q_k; n_k \neq 0, \tag{6}$$

$$2) \sum_{i=1}^{n_k} S_{g_{k^{i-1}}, r_k^i} + s_{g_k^n k,0} \leq S_k; n_k \neq 0, \tag{7}$$

$$3) G_{k_1} \cap G_{k_2} = \emptyset; k_1 \neq k_2, \tag{8}$$

$$4) \sum_{k=1}^{k} G_k = \{1,2,\dots,L\}; 0 \neq n_k \leq L, \sum_{k=1}^{K} n_k = l, \tag{9}$$

The optimization goal is as follows:

$$\min Z = \sum_{k=1}^{k} \left[\sum_{i=1}^{n_k} s_{g_k^{i-1}, r_k^i} + s_{g_k^n,0} \right] \circ sgn\, n_k, \tag{10}$$

where

$$sgn\, n_k = \begin{cases} 0, & n_k \geq 1 \\ 1, & n_k = 0. \end{cases} \tag{11}$$

The update rule is:

$$\tau_{ij}(t+s) = \rho \circ \tau_{ij}(t) + \Delta\tau_{ij}, \tag{12}$$

$$\Delta\tau_{ij} = \sum_{k=1}^{K} \Delta\tau_{ij}^k. \tag{13}$$

By combining the two algorithms to solve the problem of logistics optimization, the optimal solution of the path can be calculated, and the advantages of the two algorithms can be fully exploited to avoid some defects. The convergence curves of the two at each moment are shown in Figure 1.

The basic idea of the genetic ant colony algorithm is to calculate the minimum total convergence time first; before the most appropriate time, using the good randomness of the genetic algorithm and its faster convergence rate, the ant colony algorithm has stronger parallel processing capacity and higher efficiency and can be applied for the exploration of the optimal path in logistics and distribution.

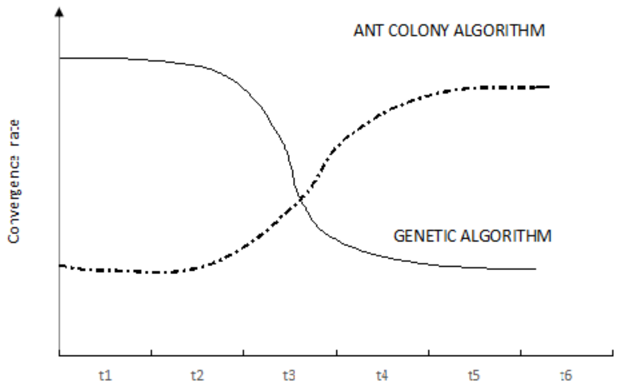

Figure 1: Curves of convergence rate

2. Overview of logistics distribution problems

Logistics needs to be organized and implemented in detail. In the general business sense, logistics and distribution is the management process between logistics [15] so as to meet the requirements of customers or enterprises. Logistics management objects cover food, materials, animals, equipment and liquids as well as abstract items such as time and information. Physical logistics usually involves the integration of information flow, material handling, production, packaging, inventory, transportation, warehousing and transport safety. Logistics distribution problem is part of the supply chain management, the distribution organizational procedures formulated to complete the distribution task and the basic content of system management [16]. The main flow of logistics is shown in Figure 2.

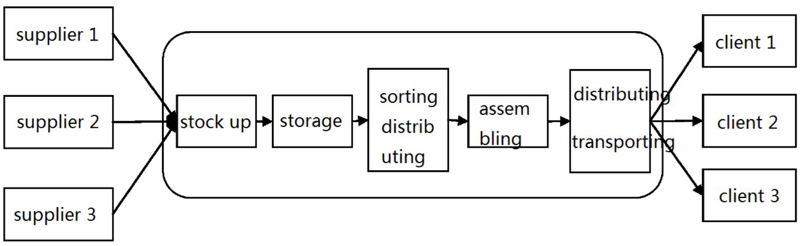

Figure 2: Logistics distribution flow chart

As shown in Figure 2, logistics distribution is systematic and orderly, and whether the distribution path is reasonable has great impact on distribution rate and cost. Therefore, taking a reasonable method to determine the distribution path is very important work in the distribution process [17].

3. Experimental simulation and analysis

To verify the practical feasibility of the optimized algorithm, this study simulates the logistics distribution process in Beijing. The distribution programs of 10 districts in Beijing is selected (specific orientation is simulated according to Google map, with variations), which are Xicheng, Dongcheng, Haidian, Chaoyang, Fengtai, Mentougou, Shijingshan, Fangshan, Tongzhou, Daxing (numbered $0, 1, 2, \ldots, 9$), with the following assumptions:

(1) The distance from the distribution center to the city where the customer is located and the amount of tasks that the city needs to deliver are known.

(2) Ignore the impact of weather, traffic and other factors on transport; there are interconnected roads between cities.

(3) All customer demand form is the same, with land transport adopted.

(4) Take Xicheng District as the center, with star connection as the starting connection mode (as shown in Figure 3).

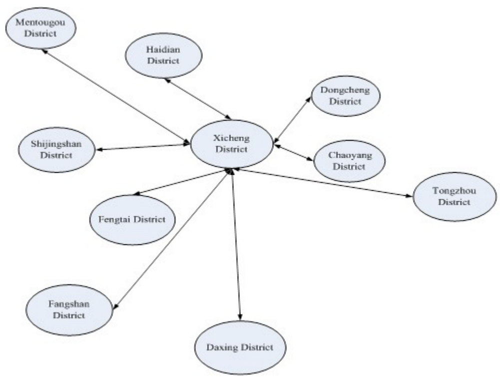

Figure 3: The logistics distribution network map in Beijing

The logistics distribution network map in Beijing

	0	1	2	3	4	5	6	7	8	9
0	0	7.3	11.2	8.1	14.2	30.5	16.1	32.4	26.6	23.3
1	7.3	0	15.1	4.6	19.7	29.7	21.7	38.9	25.7	29.1
2	11.2	15.1	0	18.1	15.2	23.7	14.2	33.7	37.5	29.9
3	8.1	4.6	18.1	0	22.9	37.1	23.9	42.7	20.4	32.3
4	14.2	19.7	15.2	22.9	0	24.6	11.2	22.7	38.7	21.1
5	30.5	29.7	23.7	37.1	24.6	0	13.9	30.3	58.9	41.9
6	16.1	21.7	14.2	23.9	11.2	13.9	0	23.7	45.8	29.9
7	32.4	38.9	33.7	42.7	22.7	30.3	23.7	0	59.9	26.3
8	26.6	25.7	37.5	20.4	38.7	58.9	45.8	59.9	0	47.1
9	23.3	29.1	29.9	32.3	21.1	41.2	29.9	26.3	47.1	0

Table 1. Distance matrix between districts in Beijing (in kilometers)

Assume that the distance between the distribution points is shown in Table 1. A total of 10 vehicles (a maximum load capacity of 2 tons) need to be deployed for distribution, all of which starts form Xicheng District and returns to Xicheng District from the original path after distribution. Therefore, the total vehicle delivery distance is:

$$L = \sum_{i-1}^{n} l_{oi},$$

where l_{oi} refers to the distance between the Xicheng District to the i-th district and the total distance is 339.4 km. In order to minimize the delivery time, shorten the distance, improve efficiency as much as possible, this paper applies the improved algorithm to optimize the actual distribution path in Beijing. First of all, the area around the Xicheng District is divided into three areas by the direction, which are then optimized accordingly, as shown in figure 4. The distance between the starting point of Xicheng District and the distribution points of other districts and the distance between districts are shown in table 1.

Target description: minimum travel distance: $\min Z$.

Description of the constraints:

(1) The maximum carrying capacity of the distribution vehicle is $q = 10$ tons.

(2) The amount of goods required in each district is $u_i = 2$ tons.

(3) Each district uses only one vehicle.

(4) After distribution, each vehicle must return to the cargo center of Xicheng District.

The other parameters are initialized as follows: $\alpha = 1, \beta = 5, \rho = 0.7, Q = 5$, maximum number of iterations $NC = 200$. Run the genetic ant colony algorithm, the solutions are: the number of vehicles = 3, the total vehicle travel distance is 289.3 km. The optimized path is shown in Figure 4.

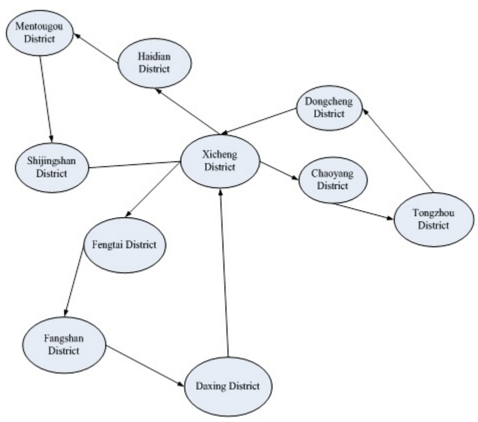

Figure 4: Logistics distribution network optimization diagram in Beijing

The optimized algorithm optimized the distribution path in Beijing, with the number of vehicles required for delivery reduced from 10 to 3 and the total distance traveled by the vehicle shorted from 339.4 kilometers to 289.3 kilometers, which effectively reduced the cost of logistics courier companies. Therefore, the algorithm has practical application value.

4. Conclusion

With the development of market economy, the logistics and distribution industry develops rapidly and more and more enterprises see the importance of logistics distribution in their production and sales process. To achieve the purpose of the vehicle's energy-saving and emission reduction, the key is to achieve the optimization of the logistics and distribution path [18]. The genetic ant colony algorithm combines the advantages of both, making it more flexible and more widely used.

In this paper, the ant colony algorithm and the genetic algorithm are effectively combined to explore the optimization of the transport vehicle path. The experimental results showed that the proposed algorithm not only solved the redundancy of the genetic algorithm which was easy to occur in the loop phenomenon, but also could solve the shortcomings of the early loop iteration of the algorithm. Still, shortcomings exist in this algorithm. For example, many actual influential factors are neglected in the experiment, which in fact play certain roles in real operation. Therefore, further studies are needed in the near future.

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